SCIENCE CHINA
Information Sciences

• LETTER •

July 2019, Vol. 62 070212:1–070212:3
https://doi.org/10.1007/s11432-018-9729-5

Special Focus on Pigeon-Inspired Optimization

A pigeon-inspired optimization algorithm for many-objective optimization problems

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Received 13 August 2018/Accepted 30 November 2018/Published online 26 February 2019

Citation Cui Z H, Zhang J J, Wang Y C, et al. A pigeon-inspired optimization algorithm for many-objective optimization problems. Sci China Inf Sci, 2019, 62(7): 070212, https://doi.org/10.1007/s11432-018-9729-5

Dear editor,

Swarm intelligence optimization algorithms are inspired by the behaviour of biological groups in nature. Such algorithms have the advantages of a clear structure, simple operation, comprehensible principles, strong parallelism, effective search abilities, and strong robustness. They can effectively solve difficult problems that traditional methods cannot. Pigeon-inspired optimization (PIO), a novel biomimetic swarm intelligence optimization algorithm, was proposed by Duan and Qiao in 2014 [1]. The original purpose of the algorithm was to simulate pigeons' homing behaviour using magnetic fields and landmarks as inputs. However, the PIO algorithm mentioned above is only applicable to a single objective optimization problems. To solve more complex, real-life problems, Qiu and Duan [2] proposed a multi-objective pigeon-inspired optimization (MPIO) to make the PIO suitable for solving multi-objective optimization problems (MOPs), and it was successfully applied to the parameter design of a brushless direct current motor. Still, the MPIO proposed by Qiu and Duan was designed to tackle MOPs with only two or three objectives. With an increase in the number and dimensions of objective functions, the applicability of MPIO decreases. In other words, MPIO is not suitable for solving many-objective optimization problems (MaOPs). To overcome this limitation, this study aims to propose a pigeon-inspired optimization algorithm for a many-objective optimization problem (MaPIO).

First, we establish an external archive to store the best solution that is continuously generated during the evolution of the population. To overcome limitations of both Pareto ranking and decomposition in MaOPs, we adopt the selection mechanism balanceable fitness estimation (BFE) approach [3]. The BFE approach combines the convergence distance and the diversity distance of each individual and has been proven to achieve promised performance, which aims to strengthen selection pressure in approaching the true Pareto-optimal fronts (PFs) of MaOPs. Please refer to [3] for the BFE approach.

Next, we improve the original MPIO of the velocity update equation to make the algorithm applicable for solving MaOPs. The new velocity update equation can provide another search direction (such as the evolutionary direction from the center-position pointing pigeon to the global-best one) and generate greater disturbance. The new

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velocity and position update equation is as follows:

$$\begin{aligned} V_i(t) =& V_i(t-1)\cdot \mathrm{e}^{-Rt} \\ &+ r_1\cdot r_2\cdot \mathrm{tr}\cdot (1-\log_T^t)\cdot (X_g - X_i(t)) \\ &+ r_3\cdot r_4\cdot \mathrm{tr}\cdot \log_T^t\cdot (X_c - X_i(t)) \\ &+ r_5\cdot r_6\cdot (X_g - X_c), \\ X_i(t) =& X_i(t-1) + V_i(t), \end{aligned} \tag{1}$$

where t is the number of the current iteration, T is the maximum number of iterations, R is the map and the compass factor, tr is the transition factor, and X_g is the positional information of the global-best pigeons. The global-best pigeons are selected randomly from the top ten percent of the external archive with better BFE values. From the closed interval from zero to one, let r_1, r_3 and r_5 be three uniformly distributed random numbers. Define the three learning-update factors r_2, r_4 and r_6 as follows:

$$r_i = \begin{cases} 0, \ 0 < \mathrm{rand}() \leqslant \frac{1}{M}, \\ 1, \ \frac{1}{M} < \mathrm{rand}() \leqslant 1. \end{cases} \tag{2}$$

In this definition, rand() is a random number in [0, 1] and M is the number of objective functions. When the value of any learning update factor is zero, $r_i = 0$, the i-th individual $X_i(t)$ will not learn and therefore will not update. When $r_i = 1$, the i-th individual $X_i(t)$ will learn and make the corresponding update by introducing parameter M to dynamically adjust the selection probability. This also makes it possible to deal with the optimization problem of different objective numbers.

Assume that every pigeon can fly straight to the destination. X_c is the center of the positions of a group of pigeons at the t-th iteration, which is calculated as follows:

$$X_c = \frac{\sum_{j=1}^{n_1^x} S_{1j}^X}{n_1^x}, \tag{3}$$

where S_{1j}^X is the j-th individual in the first ranking archive S_1^X according to the pareto sorting scheme, and n_1^x is the number of the first ranking archive.

To further enhance the solution quality in the external archive, MaPIO adopts an evolutionary search strategy, including simulated binary crossover (SBX) and polynomial mutation (PM). The use of SBX and PM enables MaPIO to further the non-dominated solutions such that some of them are maintained in the external archive using the BFE method. SBX and PM have been widely applied to solve MaOPs and are expected to address the potential insufficiency of some MaOPs to effectively generate non-dominated solutions. At the same time, to retain best solutions in the external archive, the external archive needs to be updated so that the search direction can be effectively guided to approximate the true PF. The updating strategy is performed as follows. The new solution generated will be compared with the original one in the external archive. If the new solution is superior to the original solution, the new solution will be treated as a non-dominated solution. If the original solution is superior to the new solution, the original solution will be treated as a non-dominant solution. Sorting by BFE value, the dominated solution will be removed from the external archive. The procedure here described will be continued until the prescribed size of the external archive is met.

Experimental simulation. To verify the performance of MaPIO, we selected five algorithms with excellent performance, namely the NSGA-III [4], GrEA [5], HypE [6], KnEA [7] and MOEA/D [8]. We compared these five algorithms with MaPIO on DTLZ and WFG test functions with 4–10 objectives. For each test function, we ran an experiment 20 times with each algorithm. All parameters of these algorithms were set as suggested in their original references to obtain a statistically sound conclusion. The population size settings of all algorithms were consistent in principle. For MOEA/D and NSGA-III, the two-layer reference point strategy was adopted according to the suggestions of the developers offered in the original references. The segmentation number parameters in GrEA are detailed in [5]. The setting of parameter T in KnEA to control the ratio of non-dominant knee points can be found in [7]. As for MaPIO, the transition factor was set to 1; the map and compass factor were each set to 0.3 according to the suggestions of the algorithm developers.

To visually understand the solution distribution, Figure 1 shows the Pareto fronts obtained by MaPIO and the other five MOEAs, respectively, for an eight-objective DTLZ2 instance. The Pareto fronts obtained by NSGA-III, MOEA/D, and MaPIO exhibit a better distribution than the proposed algorithm, and that obtained by GrEA, HypE, and KnEA showed a poor distribution. However, the Pareto front obtained by MaPIO is distributed between them, suggesting that NSGA-III and MOEA/D pay more attention to diversity whereas GrEA, HypE, and KnEA pay more attention to convergence. Appendix A shows the comparisons of results of MaPIO and five competitive MOEAs on DTLZ and WFG. In light of the discussion above, we conclude that MaPIO demonstrated a good balance of diversity and convergence.

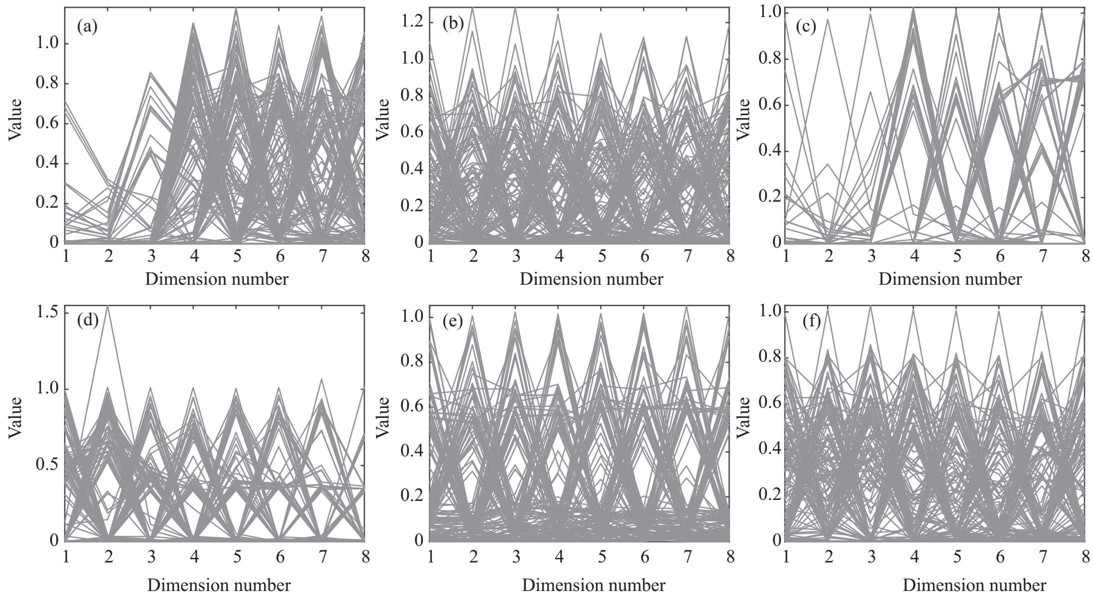

Figure 1 Pareto front obtained by different algorithms on the eight-objective DTLZ2 instance. (a) NSGAIII on DTLZ2; (b) GrEA on DTLZ2; (c) HypE on DTLZ2; (d) KnEA on DTLZ2; (e) MOEAD on DTLZ2; (f) MaPIO on DTLZ2.

Conclusion. Herein, we proposed an MaPIO algorithm to apply PIO to solve MaOPs. First, the BFE approach was employed to balance population convergence and diversity. Then, to provide an extra search direction pointing from the centre position to the global-best positions, we designed a new velocity and position updating equation, which also addressed the problem of the number of objective functions being drastically altered. In addition, to further enhance the solution quality in the external archive, evolutionary operators such as SBX and PM were employed in MaPIO to further guide non-dominated solutions. Finally, to verify the performance of the proposed MaPIO algorithm, the MaPIO was compared with five competing many-objective evolutionary algorithms. The experimental results indicated that the MaPIO algorithm has great promise in solving MaOPs.

Acknowledgements This work was supported by National Natural Science Foundation of China (Grant Nos. 61806138, U1636220, 61663028, 61702040), Natural Science Foundation of Shanxi Province (Grant No. 201801D121127), Scientific and Technological Innovation Team of Shanxi Province (Grant No. 201805D131007), Ph.D. Research Startup Foundation of Taiyuan University of Science and Technology (Grant No. 20182002), and Beijing Natural Science Foundation (Grant No. 4174089).

Supporting information Appendix A. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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